

Neural geo-spatial model: a strategic planning tool for the urban transportation

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Abstract

A strategic planning model for urban transportation analysis is presented. This model is based on the incorporation and representation of the land use-transportation system interaction under a spatial-temporal approach to forecast travel demand within urban areas. This conception becomes possible due to the integration of Neural Networks (NN), Geographical Information Systems (GIS) and Remote Sensing (RS). A case study in Boston Metropolitan Area was conducted to verify the efficiency of the model and evaluate the best NN structure and also changes in the hidden and output layers were simulated. A recognition rate of 94% was reached expressing the successful definition of the NN. It does mean that the integration of techniques used in this model is appropriated.

1 Introduction

Only recently, changes in urban transportation planning towards a strategic approach in opposition to an operational one have been observed. After a long period predominantly geared towards evaluating traffic congestion and road construction in day-to-day operations, planning agencies shifted their focus to longer term (future visions) and to developing strategies to obtain more integrated transportation systems by exploring new technological potentials [1]. As a result of these changes, modeling techniques in a strategic planning context have assumed a complementary role in order to provide additional information in overcoming uncertainties. According to Ng [2], once the strategic approach is based on discussion and dialogue between internal and external actors, analytical

work does not assume primary importance as verified in traditional planning. In this sense, strategies are formulated and evaluated regarding multiple scenarios and alternatives in order to take advantage of available resources.

Nevertheless, strategic planning in transportation is still applying modeling techniques based upon an operational context and formulation. As reported by Meyer [3], there were some strategic planning initiatives, but Tyndall *et al* [4] concluded that few of these early efforts were implemented. This situation can be clearly understood if the nature and concept of traditional modeling that is extensively applied are examined. Originally developed to evaluate network problems using socioeconomic data and levels of aggregation for microanalysis, modeling techniques turned out to be inadequate in providing additional information according to the level and flexibility required in a strategic approach. Moreover, they have been criticized due to the massive and costly requirements for application in real problems [5] and due to the non-incorporation of the dynamic and realistic dimension of urban reality [6].

In this paper, we present a Neural Geo-Spatial model (NGSM) specifically aimed towards strategic planning in order to generate information on travel demand within urban areas. The demand information is quantified in levels (high – medium – low) that express the intensity of the movements performed daily. Once the levels of demand are obtained, participation and discussion among the actors in the evaluation of the urban evolution and the formulation of future strategies become possible. In addition, this model incorporates the urban dynamic affecting the travel process according to a non-linear modeling through the combination of RS data, GIS and NN.

This paper is organized into five sections. After this introduction, section two briefly describes the role of our model in a strategic planning context in order to explain its relevance and inclusion. We concentrate on the description of the NGSM in section three. In section four, the case study carried out in the Boston Metropolitan Area in order to verify the model's efficiency is presented. Finally, we discuss the main points developed in this research as well as the perspectives for future improvements.

2 NGSM in a strategic planning context

Five steps compose a typical strategic planning process. Firstly, environmental scanning is processed in order to identify purposes, participants, time commitments and the appropriate organizational structure. Next, in order to detect difficulties influencing the activities and the achievement of future perspectives, strategic issues are identified. The third step is geared towards developing strategies by exploiting strengths and overcoming weaknesses. A comparative evaluation in the next step leads to the feasibility assessment, which ranks the desirability of different strategies. Finally, the implementation step discusses the barriers and key issues when dealing with real condition [2].

Throughout this process the knowledge generated from information is an essential element. As pointed out by Schaefer [7], through information support during the process, strategic decisions can be improved. Moreover, it is clear that

this information has to be a dynamic element interacting with the stages in the process. In urban transportation, such information is related to spatial reality where complex interactions occur daily and consequently it has to be carefully incorporated.

The NGSM intends to incorporate information about the urban movements into the strategic planning process. As shown in figure 1, the model is linked to the Identification of strategic issues, Strategic options and Feasibility assessment steps. During these steps, it is expected that transportation planners have basic knowledge on daily movements within the urban area as well as the evolution process (past conditions) and future scenarios. In this sense, the NGSM is an instrument to be used mainly to ensure that planners have the correct notion on how, when and where transportation systems must be re-organized and improved. This notion is acquired through the forecasting of travel demand based upon a qualitative perspective of movements.

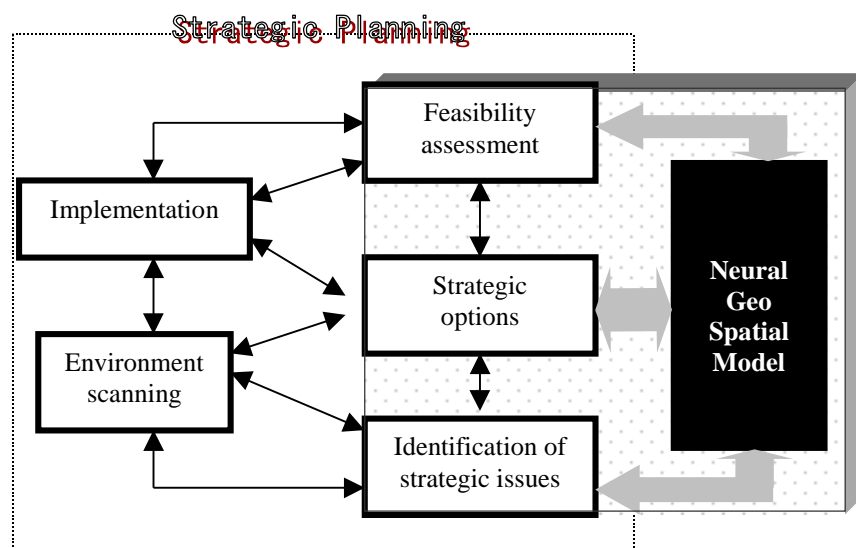


Figure 1: Integrating Neural Geo-Spatial model to the strategic planning

3 NGSM formulation

The concept of the NGSM focuses on the forecasting of travel demand for strategic planning activities. Consequently, it simultaneously concentrates on the incorporation of the urban dynamic affecting travel demand, the establishment of evaluations according to a macro-level and the development of an efficient (few data requirements) modeling structure. In this sense, the model is based on previous work conducted by Rodrigue [8] and Taco *et al.* [9]. The former presented an innovative and theoretical concept, considering economic structure, population, accessibility and spatial interactions in order to forecast a land use-

transportation system that makes use of NN. However, this concept is based principally on socioeconomic data and concerned about general urban planning. At the same time, Taco *et al.* [9] elaborated and applied a travel generation model contemplating land use patterns extracted from aerial photograph images focused on the incorporation of the land use-transportation interaction by exploring the integration of RS and GIS. Nevertheless, Taco's model did not evaluate dynamic changes and the interactions between patterns and it just performed the modeling of the travel generation phase.

In the NGSM, these two distinct approaches are brought together in order to establish a travel-forecast model integrating NN, RS and GIS. RS images are processed in GIS to obtain indicators related to land use-transportation system interactions such as areas of the patterns, extension of modes and spatial location. From this data, NN is used to forecast the trips within the urban area.

The NGSM's formulation starts by considering an urban area as a locational arrangement of activities, where people move from one place to another to take part in socioeconomic events [10]. These activities are represented by land use patterns that occupy the earth's surface and are separated by distance. Therefore, trips can be conceived as an imbalance in land use patterns in different locations inside the urban area. On the other side of the travel process, the transportation system acts as a supply and inducing element. Through the use of transportation systems (streets, roads, highways, bus lines, subway, train, etc), the interaction between land use patterns can be processed [8]. In addition to its supply role, the transportation system can be used to induce development. This means that a change in accessibility determines a change in the value of land and may affect the way land is currently used. From a temporal perspective, if such change does occur the travel process will change [10].

In terms of this backdrop, it is assumed that the occupied area and the extension of each mode can quantify land use patterns and transportation systems, respectively. Thus, considering an urban area that is divided into Homogenous Aggregated Sectors (*HAS*), and which consists of a set of land use patterns, Trips (T_{ij}) between a pair of *HAS* pairs are verified, where i and j denote the origin and destination, respectively. Land use is represented by occupied area (square meters) of each pattern in each *HAS*, which is assigned to rlu_{HAS} (residential land use), clu_{HAS} (commercial land use) and slu_{HAS} (service land use). Transportation system is characterized by the extension of each mode (meters) in each *HAS*, which is associated to rts_{HAS} (road transportation system), bts_{HAS} (bus transportation system), sts_{HAS} (subway transportation system) and tts_{HAS} (train transportation system). In order to represent the spatial distribution of a pair of *HAS*, the distance d_{ij} is defined (meters).

In a feedforward Multilayer Perceptron (MLP), the input and output vectors are established [11]. The input vector (X) is defined as

$$X_{ij}=(rlu_i, clu_i, slu_i, rts_i, bts_i, sts_i, tts_i, rlu_j, clu_j, slu_j, rts_j, bts_j, sts_j, tts_j, d_{ij}) \quad (1)$$

As the NN is assigned as a pattern classifier, the final output of the model classifies the forecasted movements in levels such as high, medium-high,

medium, medium-low and low. The output vector of the training/testing data set has to be modified. So, T_{ij} is linearly quantized (classified according to pre-established intervals) in z levels and represented by z output units y defined as

$$y_k = \begin{cases} 1.0, & \alpha_k \leq T_{ij} < \beta_k \\ 0.0, & \text{otherwise} \end{cases} \quad \text{where } k \in (1, 2, \dots, z) \quad (2)$$

where α_k and β_k are the minimum and maximum T_{ij} values that define the k level. It is clear that the number of output units in the NN structure is directly related to the number of z levels.

This formulation refers to the spatial forecast, i.e., without variations along time. At the current stage of this research, the NGSM is developed to forecast travel demand within the urban area. Obviously, the temporal variation is essential for strategic planning, but first it is essential to evaluate if the selected variables are suitable to model the land use - transportation system - travel demand interaction. It is in light of this, the case study works toward such an evaluation.

4 Case study

The case study was conducted in the Boston Metropolitan Area (Massachusetts State – USA), which covers about 3580 square kilometers and where nearly three million people live. A study area in the South Boston area, near to the Boston Medical Center, and which involves seventeen Traffic Zones (TZ), was selected. It was assumed that the TZ 's were equivalent to the HAS definition. The study area is mainly occupied by residential land use and it is located very near to downtown.

RS and transportation system data were obtained from the *MassGIS* database. In this database, data was projected onto the Massachusetts State plane Mainland Zone (FIPZONE 2001) coordinate system, Datum NAD83, unit meters. Black and white digital orthophotos produced in 1992 in 1:5000 scale were used. Also, bus route maps from the Metropolitan Boston Transportation Authority (MBTA) were incorporated into Transportation data. Moreover, the Central Transportation Planning Staff (CTPS) provided access to travel data related to the 1990 survey that involves all purpose trips as well as the TZ definition.

In the next section, GIS database construction activities are described. Then following this, NN experiments and results are presented.

4.1 GIS database

By using GIS software, firstly, TZ s were defined as shown in figure 2. Next, land use patterns were obtained by following the *United States Geological Service*

(USGS) classification system [12] and Taco's methodology [9]. Up to Level II (Residential, Commercial and Services) was analyzed according to the model's requirements (see item 2). Then, the transportation system was transformed into digital format inside the GIS database.

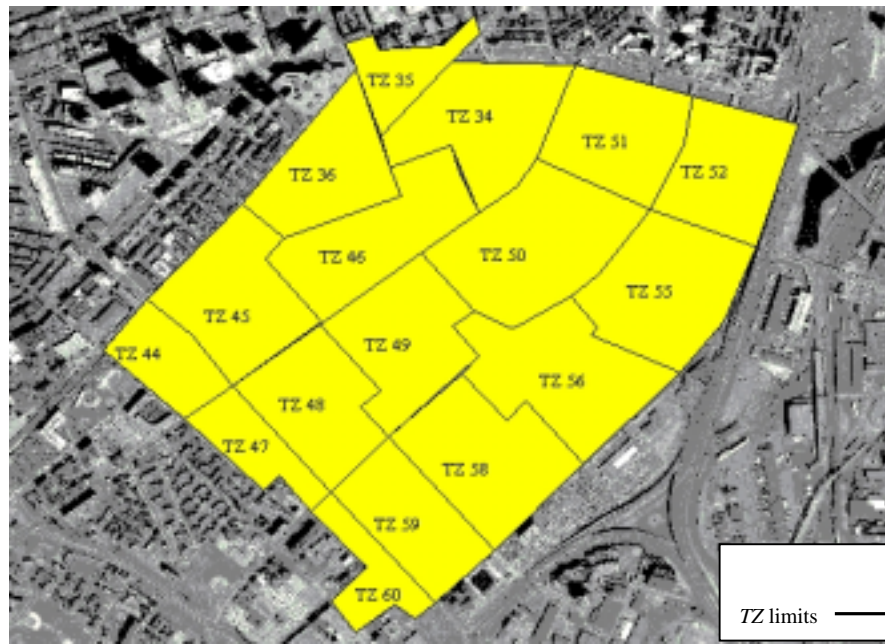


Figure 2: Study area with the selected TZ

4.2 NN experiments and results

From the spatial queries, a data set formed by 289 vectors was generated. The input vector X was normalized using

$$xn_c = -1 + 2 \left[\frac{(x_c - x_c^{\min})}{(x_c^{\max} - x_c^{\min})} \right] \quad (3)$$

where x_c is the value from X input vector for characteristic c , according to eqn (1), xn_c is the normalized value and x_c^{\min} and x_c^{\max} are the minimum and maximum values for the related characteristic.

Using this normalized data set, the training (75%) and testing (25%) data sets randomly selected were defined, so 216 and 73 vectors were assigned to training and test sets, respectively. As established by eqn (1), the input layer should have 15 units. It was determined that the output layer should have 5 units, i.e. $z=5$ levels (high, high-medium, medium, medium-low, low travel demand). In this sense, the T matrix was quantized according to eqn (2).

By applying a backpropagation algorithm, the networks were trained until a Minimum Square Error (*MSE*) in the test set was obtained. The best result (*MSE*= 0.15) was for a four-layer structure with 15 and 7 units in the hidden layers. This represents a recognition rate of 94.5%. By analyzing in detail the forecasted results, it can be verified that the errors occurred in five testing vectors. These vectors were related to levels 2, 3 and 4. At the same time, all the test vectors related to level 5 ($0 \leq T_{ij} \leq 14$) were correctly forecasted.

The composition of the training set can explain the NN's performance. It can be observed that we are dealing with a very imbalanced problem since there is a great concentration of data on level 5 (252 vectors – 87% of the total), making the same the dominant level. Meanwhile, levels 1, 2, 3 and 4 have only 1, 3, 5 and 28 vectors, respectively. This composition led to the construction of training and testing data sets that resulted in NN's efficiency just for those vectors in level 5.

Despite the high recognition rate, the final results were compromised by the data's composition. This problem has been observed in real-life data and some research has been developed in order to solve the same. Some efforts have been made towards changing the backpropagation algorithm to avoid such imbalanced training [13]. Alternatively, we propose in this work a solution focused on the treatment of training/test data in order to obtain a smooth distribution of the vectors. In this sense, it is necessary to add some data to those levels, which are formed by few vectors (levels 1,2,3,4) and select some from level 5.

It was defined that 40 and 10 vectors of each level would form the training and testing data, respectively. First, new data was estimated for those vectors related to levels 1, 2, 3 and 4 by adding gaussian noise with average zero and variance 0.001 to those existing vectors, generating new noisy versions. This operation was performed in order to supply the NN training with vectors highly correlated to the original ones. Next, the number of vectors in the level 5 was reduced creating a new set of more representative vectors using the *LBG* algorithm [14]. The *LBG* aims to design *quasi-optimum* codebooks in vector quantization based coding systems. This was applied to create 50 template vectors for level 5 by minimizing the *MSE* of the representation for all vectors of this level.

Using this balanced data training set, the best result (*MSE*=0.10 and recognition rate 94.0%) was obtained for a four-layer NN with 15 and 7 units in the hidden layers. The balanced data provided a better modeling for those levels that had only few samples in the original imbalanced training data set. Table 1 shows the performance reached in the test set. In all categories, the NN was able to forecast correctly the majority of testing vectors. In the vectors that resulted in an incorrect forecast, it can be noticed that one or more characteristics of the input vector (*X*) are zero. Specifically, the errors were related to trips that do not contain train and subway transportation systems. Physically, these errors express how difficult it is for the NN to obtain an expected result without information on the transportation system.

Table 1 – Recognition rate for levels

	Level 1	Level 2	Level 3	Level 4	Level 5	Final
Imbalanced data	0%	0%	0%	33%	100%	94.5%
Balanced data	100%	100%	100%	80%	90%	94.0%

5 Conclusion

The development of the NGSM aims to contribute to transportation planning from different perspectives. Firstly, strategic planning activities require instruments providing information about future scenarios in the transportation system. In terms of the travel-forecast problem specifically, the NGSM is a flexible and direct instrument generating qualitative information on urban displacements. Then, given that it is dealing with a complex dynamic as exists in urban areas, transportation modeling must not be limited to linear formulations such as traditional approaches conducted until now. In this sense, the NGSM is based on a non-linear parallel processing technique, which extends the analysis to the land use – transportation system interaction. Finally, the use of alternative data sources such as RS promotes the incorporation of urban features in transportation modeling and a new panorama for data collection.

Regarding particularly the NGSM's formulation, the results of the simulations showed the model's efficiency in representing the travel demand process. A 94% recognition rate that provided a considerable modeling of movements within the urban area was achieved. However, in order to obtain this rate it was necessary to conduct a pre-processing activity, which transformed original data into a balanced set. Such treatment became fundamental to the NN training process due to the nature of the data. It was noticed that the more trips there were, the less the number of zones verified and vice-versa. Thus, the balanced set of data just provided “new” samples in order to create better conditions for the NN learning process. This procedure is common for other NN applications such as meteorology and does not interfere in the final result at all.

As this is research still being conducted, there are some activities that we intend to perform from now on in order to improve the NGSM. After the development of the NGSM's spatial dimension, the next step is the conception and simulation of the temporal module. It is our intention to use the NGSM to forecast travel demand for future scenarios based on temporal series data. Nonetheless, it has been very difficult to find an urban area that possesses, all at the same time, aerial photographs/satellite image, transportation system data and travel data. In addition to the temporal module, we intend to conduct experiments on the aggregation level of data and the automatic obtaining of land use patterns.

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